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Assessing the effects of climate change on water quality of plateau deep-water lake - A study case of Hongfeng Lake

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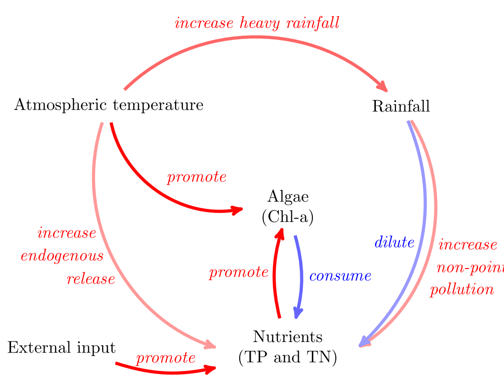
HIGHLIGHTS

- A Back Propagation Artificial Neural Networks (BPANN) proxy model was proposed.
- Climate change is expected to cause algal blooms and nutrient enrichment, notwithstanding weak effects on nutrients.
- Random heavy precipitation events will increase nitrogen source pollution.
- Controlling external nutrient inputs is key to mitigating eutrophication in Hongfeng Lake.

GRAPHICAL ABSTRACT



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ABSTRACT

Climate change-related temperature increases and sea level rise have a significant impact on the atmosphere, hydrosphere, biosphere, and anthroposphere. Impacts on ecosystems will mostly occur over the long term and short-term effects may consequently attract comparatively less attention from researchers and decision-makers. In this study, we investigate eight meteorological factors and eleven water quality indicators of deep-water lakes in the Yunnan-Guizhou Plateau in southwestern China. A robust proxy model based on a seven-year dataset (2010–2016) was established to predict the effects of climate change on water quality in Hongfeng Lake over the coming years. Perturbation analysis revealed that global warming has a more significant effect on chlorophyll a levels than on total phosphorus or total nitrogen in the lake area, and that external nutrient loading is a key factor aggravating eutrophication. Non-point source pollution induced by heavy precipitation will likely lead to an increase in total nitrogen and the lake may become more phosphorus-restricted. Reducing external inputs and controlling endogenous releases will help alleviate eutrophication.

1. Introduction

Water resources are essential to support biodiversity and provide social and economic benefits to humans (Bérenger and Verdier–Chouchane, 2007; Hajkowicz, 2006). Eutrophication, mainly caused by excessive inputs of nitrogen and phosphorus (Carpenter et al., 1998), is one of the most challenging environmental problems that surface water bodies are facing at present (Smith and Schindler, 2009; Yang et al., 2017). Excessive algal growth under eutrophic conditions could eventually lead to significant deterioration of the waterbody (Boeykens et al., 2017).

Climate change may exacerbate these problems (Chapra et al., 2017), for example, by increasing water temperatures or by

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increasing rainfall, impacting nutrient loads from the catchment (Couture et al., 2018). Flooding will cause fertilizer and manure that have been applied to crops to be released more rapidly downstream and into the atmosphere (Davidson et al., 2011). Meanwhile, precipitation is expected to decline in some areas, such as southern Europe. Regional climate models project a 17% decrease in summer precipitation in these areas until 2100 (van der Linden et al., 2015). More frequent drought events may also lead to drops in lake levels, aggravating eutrophication. It is therefore necessary to quantitatively assess the effects of climate change on water quality of eutrophic waterbodies.

Water quality modelling is a powerful tool for comprehensive interpretation of complex water quality interactions (Ambrose et al., 2009; Kim et al., 2017). However, given limited availability of field data and system complexity, use of these modelling techniques is often restricted. Due to complex interactions of physical, chemical, and biological parameters affecting growth and accumulation of biomass, traditional statistical models (e.g. multiple linear regression, autoregressive moving average models) are also problematic (Recknagel et al., 2013; Xiao et al., 2017). A model may not be able to accurately predict water quality in the long term because of the complexity of the water environment. A robust short-term assessment and prediction model is therefore needed.

Artificial Neural Networks (ANNs), mathematical models that mimic the structure and function of the biological central nervous system, are used to model complex relationships between inputs and outputs and find patterns in data (Sen Gupta et al., 1985; Bansilal et al., 2003); they can even handle small and incomplete datasets. Application of ANNs for environmental and water resources modelling has become increasingly popular since the early 1990s (Wu et al., 2014).

Backpropagation (BP), for networks of neuronlike units, has been proposed as a new learning procedure (Rumerlhar, 1986). The procedure repeatedly adjusts the weights of connections in the network so as to minimise a measure of the difference between the actual output dataset of the network and the desired output dataset (Park and Lek, 2016). A BPANN is therefore characterised by rapid convergence, a simple structure, and good global approximation capacities, and consequently, by an absence of local minimum problems (Yang et al., 2018). BPANN is applied in this study to establish proxy models, which approximately represent complex interactions between all studied meteorological and water quality factors.

Plateau lake ecosystems in China are vulnerable to environmental changes and human disturbances because they are closed environments (Dai et al., 2017). The lakes in the Yunnan-Guizhou Plateau are mostly deep (maximum depth $>$ 155 m) and have a long retention time. The ability to purify pollutants entering the lake is weak (Yu et al., 2010). Moreover, there are many river systems in the tributaries of the lake and there is a high possibility of wastewater entering the lake from coastal factories, household sewage, and non-point source pollution. Outflow is generally low, which easily leads to accumulation of pollutants in the lake.

Hongfeng Lake, a typical plateau deep-water lake in southwest China, was selected as a case study. The Hongfeng Lake basin is in a subtropical monsoon climate zone, with rainfall mainly occurring in summer, and might be severely affected by climate change. The karst topography of the area leads to thin soil layers, extensive slopes, and susceptibility to soil erosion. More frequent storm runoff caused by climate change would carry more soil and agricultural fertilizers into rivers and lakes, causing more agricultural non-point source pollution. While biogeochemical forms and distribution of many elements (e.g. phosphorus, nitrogen, carbon, mercury) and water exchange in Hongfeng Lake have been investigated (Wang et al., 2009; He et al., 2008; Wang et al., 2016; Wu et al., 2017), the effects of climate warming on water quality have not yet been fully analysed for water-quality management purposes, partly because of the difficulties of identifying such impacts in highly dynamic systems.

Cyanobacteria in Hongfeng Lake have bloomed on many occasions before 2010. The mechanism of algal blooming is still not well understood; however, it can be noted that algal variations are closely related to chlorophyll a (Chl-a) and algae cell density, with these appearing to be the factors best reflecting algal quantity (Wu and Xu, 2011). Chl-a is probably most often used as an estimator of algal biomass (Gibson et al., 2000), with concentrations reflecting the integrated effect of many of the water quality factors that may be altered by restoration activities. Chl-a is relatively easy to measure compared to algal biomass (Boyer et al., 2009). If trends in Chl-a concentrations can be accurately simulated, they can therefore help predict algal bloom events (Wu and Xu, 2011). Total phosphorus (TP), and total nitrogen (TN), as direct indicators of eutrophication, together with Chl-a were considered to be the most important water quality indicators in this study.

The objectives of this work are: 1) to establish a robust proxy model of water quality using simple calculations with high accuracy, 2) to identify key factors controlling Chl-a, TP, and TN using the AGA-BPANN-FAST model, and 3) to assess the effects of climate change on plateau deep-water reservoirs over the next few years. The modelling exercise conducted increases knowledge of water quality interactions, contributing to the study of abatement options for reducing eutrophication.

2. Methods and materials

2.1. Site

Hongfeng Lake ($106°19'E \sim 106°28'E, 26°26'N \sim 26°35'N$) is located about 28 km west of Guiyang City, Guizhou Province, China. With an area of about 57.2 km^2, a water depth of 10.52 m, a maximum depth of about 45 m, and a storage volume of 6.01×10^8 m^3, Hongfeng Lake provides drinking water for more than 300 million people. Any slight deterioration in water quality may therefore have serious consequences.

Hongfeng Lake is mainly composed of the deeper North Lake area and the shallower South Lake area. The main four inflows are Maiweng River, Maxian River, Yangchang River, and Houliu River; the Maiweng River flows into the North Lake area, while the others flow into the South Lake area. Seven sites (Daba, Yaodong, Pianshanzhai, Huayudong, Houwu, Xijiaoshuichang, and Sanchahe) in the reservoir area were identified for monitoring of water quality. Fig. 1 shows the geographic distribution of these seven sites. The Daba, Yaodong, and Pianshanzhai sites are in the North Lake area while Houwu, Xijiaoshuichang, and Sanchahe are in the South Lake area. The Huayudong site is at the junction of the North and South Lake areas.

Monthly monitoring data from the Guizhou Environmental Monitoring Centre for a seven-year period (2010–2016) were used in this research. Water quality indicators used in this study include transparency, surface water temperature, pH, COD_{Mn}, dissolved oxygen (DO), ammonia nitrogen (NH_3-N), TP, TN, fluoride, and Chl-a.

2.2. Method

The complex relationships between meteorological and water quality factors are often referred to as functions in mathematical models. The core of establishing a water quality model is to identify a functional expression. This function may be explicit or it may be an implicit function that cannot be specifically expressed.

Typically, a certain water quality factor is selected as an output (i.e. dependent variable) and other factors are assigned as inputs (i.e. independent variables). Artificial neural networks (ANNs) can

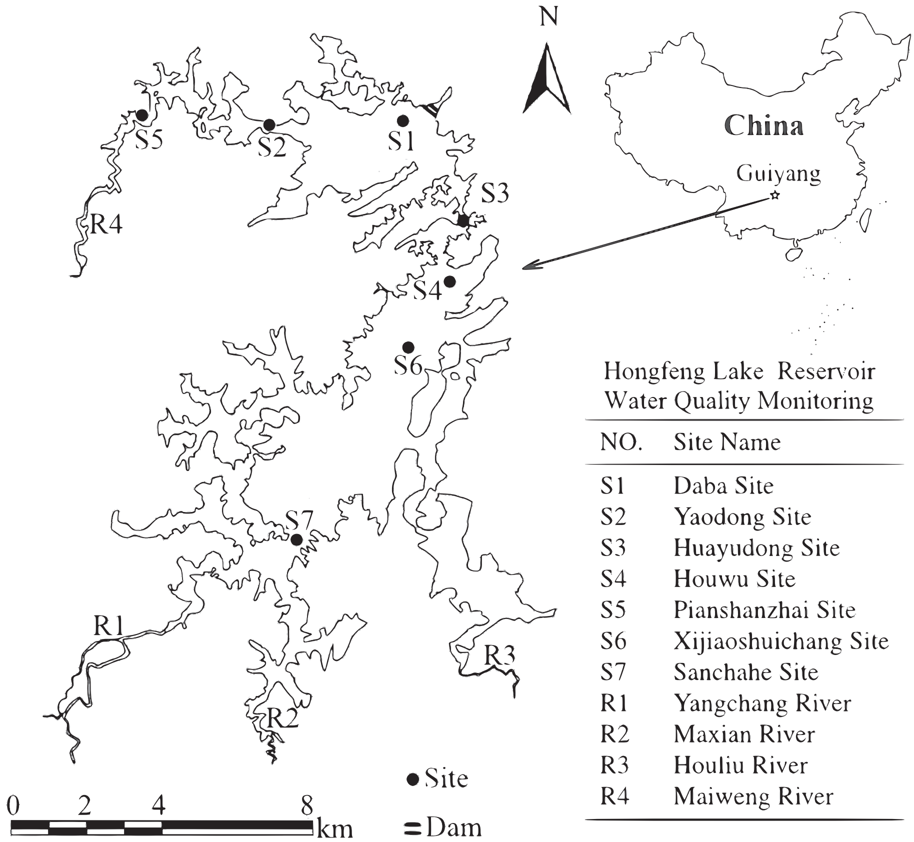

Fig. 1. Distribution of sampling sites. Hongfeng Lake is composed of the deeper North Lake area and the shallower South Lake area. The Daba (S1), Yaodong (S2), and Pianshanzhai (S5) sites are in the North Lake area while Houwu (S4), Xijiaoshuichang (S6), and Sanchahe (S7) are in the South Lake area. The Huayudong (S3) site is at the junction of the North Lake and South Lake areas.

satisfactorily model the complex relationships between meteorological and water quality factors by establishing reliable mathematical patterns between inputs and outputs. A proxy model that describes the relationship between overall factors can therefore be obtained. When some perturbation occurs in input variable data (e.g. increase in atmospheric temperature), the output changes, and this change can be quantitatively displayed. The impact of climate change on water quality factors can be quantitatively estimated by such a proxy model.

Method details are as follows:

2.2.1. Back propagation artificial neural networks (BPANN)

For a given set of samples

$$G = \{(\boldsymbol{x}, \boldsymbol{y}) : \boldsymbol{x} \in R^n, \boldsymbol{y} \in R\} \tag{1}$$

and function set

$$\{f(\boldsymbol{x}, \boldsymbol{\alpha}), \boldsymbol{\alpha} \in A\}, \tag{2}$$

where $\boldsymbol{x}$ is the input set, $\boldsymbol{y}$ is the output set, R^n is an n-dimensional real number space, and A is a parameter set. We assume that a fixed but unknown relationship F exists between $\boldsymbol{x}$ and $\boldsymbol{y}$.

Identification of the most appropriate $f(\boldsymbol{x}, \boldsymbol{\alpha})$ in the function set to approximate the unknown relationship F is referred to a regression problem and this relationship is expressed as $\boldsymbol{y} = f(\boldsymbol{x}, \boldsymbol{\alpha})$. Networks with biases, a sigmoid layer, and a linear output layer, can approximate any function F with a finite number of discontinuities (Ghwanmeh et al., 2013).

In this study, tansig and pureline transfer functions of MATLAB were used to improve model efficiency. In order to study the impact of climate change on Chl-a, TP, and TN, three different BPANN models were established. For these three models, Chl-a, TP, and TN were respectively selected as the output set, and all other meteorological variables and water quality indicators of Hongfeng Lake were selected as input datasets. There is an intrinsic link between all three models because of the complex interactions between meteorological and water quality factors. In other words, the three different proxy models essentially form a whole.

2.2.2. Augmented Dickey-Fuller test (ADF-test)

The Augmented Dickey-Fuller test (ADF-test), a time series stationarity test, is usually used to check the trend of the time series within a given time interval. Passing the ADF-test indicates that the time series data changes little during the period, that is, the time series is stationary or relatively stationary.

The basic idea of stationarity is that the probability laws that govern process behaviour do not change over time (Maindonald, 2010). In this study, time series data of eight meteorological factors and eleven water quality indicators were analysed via the ADF-test to check their stationarity. If the time series of these variables is stationary or approximately stationary, these data may in the future maintain regular changes that are similar to historical ones. It is beneficial to forecast the effects of climate change on water quality over the next few years, with the interaction between meteorological and water quality factors expected to follow a similar pattern in the coming years as in the past.

2.2.3. Cross-correlation

For two stationary time series X_t, Y_t, which have complex interactions (e.g. rainfall and TN seven-year datasets), cross-correlation is useful for determining the time delay between them. The cross-covariance and cross-correlation coefficient are then given by:

$$\gamma_{XY}(\tau) = E[(X_t - \mu_X)(Y_{t+\tau} - \mu_Y)] \tag{3}$$

$$\rho_{XY}(\tau) = \frac{1}{\sigma_X \sigma_Y} E[(X_t - \mu_X)(Y_{t+\tau} - \mu_Y)] = \frac{1}{\sigma_X \sigma_Y} \gamma_{XY}(\tau) \tag{4}$$

where $\gamma_{XY}(\tau)$ and $\rho_{XY}(\tau)$ are cross-covariance and cross-correlation coefficient respectively, τ is time delay, also known as *lag* in time series analysis, μ_X and σ_X are the mean and standard deviation of the process X_t, which are constant over time due to stationarity; and similarly for Y_t, respectively.

In this study, cross-correlation is applied to determine the hysteresis effect between rainfall and nutrients time series. After calculating the cross-correlation between the two time series, the maximum (or minimum if the series are negatively correlated) of the cross-correlation function indicates the point in time (τ) where the two series are best aligned. If τ is not zero, there is an expected hysteresis effect between them.

2.2.4. Adaptive Genetic Algorithm (AGA)

BPANNs are appropriate for precise local searches; they randomly generate a set of initial weights and use the gradient descent method to calculate the correction value of the weights until the training error reaches the target precision range. When the initial weight value is not appropriate, it tends to fall into the local minimum point; the influence of the weight on the ANN is thus evident.

Since the initial weights of ANNs are often randomly generated, each training does not guarantee optimal results. Genetic Algorithm (GA), a type of randomized search method that evolved from the evolutionary laws of the biosphere (survival of the fittest), has strong global search capabilities and has been used to ensure that the optimal solution is obtained quickly. To improve the efficiency of the algorithm, an improved Adaptive Genetic Algorithm (AGA) (Srinivas and Patnaik, 1994) was applied in this study.

The selection of the fitness function in the AGA plays an important role in finding the optimal solution and achieving a satisfactory convergence speed. In this study, the fitting error sum of squares was selected as the fitness function. Then, the set of solutions with minimum errors was obtained for initial weights. After training, the BPANN model showed good performance.

2.2.5. Bayesian regularisation

Overfitting is a common occurrence in machine learning; the model loses generalisation and is no longer applicable to other datasets that were not used to train the network. Too many correlated or extraneous inputs will increase model training time and the likelihood of overfitting (Maier and Dandy, 2000).

In this study, the Bayesian regularisation algorithm was used to avoid overfitting of the model. Bayesian methods are optimal for solving learning problems with neural networks. They can automatically select regularisation parameters and integrate the advantages of traditional BPANN and Bayesian statistics, such as high convergent rate and prior information, respectively (Burden and Winkler, 2000; Lampinen and Vehtari, 2001; Sun et al., 2005). Bayesian regularisation can handle large or small input datasets, with linear or non-linear correlations with each other, and effectively prevent high model complexity and weak generalisation ability.

2.2.6. Fourier Amplitude Sensitivity Test (FAST)

Sensitivity analysis is used to evaluate the behaviour of a model and ascertain the dependence of the outputs on input parameters (Saltelli and Bolado, 1998a). The goal is to explain how key indicators are influenced by changes in values of relevant variables.

BPANN is often considered a black box so that analysis work is relatively difficult and various methods have been explored to illustrate the role of variables in ANN models (Gevrey et al., 2003). In high-dimensional non-linear water quality models, input variables may not be independent and many traditional statistical methods do not fully use them. The Fourier Amplitude Sensitivity Test (FAST) was therefore used for sensitivity analysis of input variables, to identify the factors that contribute most to outputs.

The Fourier Amplitude Sensitivity Test (FAST), a classical global sensitivity analysis method, the theory of which comes from analysis of variance (ANOVA) and Fourier transform, has successfully been applied to many modelling problems, including non-linear models (Cukier et al., 1973). By calculating the contribution of the specified parameters to output variance, the first-order sensitivity of parameters S_i can be obtained using the following equation:

$$S_i = \frac{var_i[E(\boldsymbol{y} \mid \boldsymbol{x})]}{var(\boldsymbol{y})} \tag{5}$$

where

$$var(\boldsymbol{y}) = \frac{1}{2\pi}\int_{-\pi}^{\pi} f^2(\boldsymbol{x}(s))\mathrm{d}s - \left(\frac{1}{2\pi}\int_{-\pi}^{\pi} f(\boldsymbol{x}(s))\mathrm{d}s\right)^2 \tag{6}$$

and

$$\boldsymbol{x}(s) = \frac{1}{2} + \arcsin(\sin(\boldsymbol{\omega} s)). \tag{7}$$

The application of Parseval's theorem to the computation of Eq. (6) allows to reach the expression

$$var(\boldsymbol{y}) = 2\sum_{j=1}^{\infty}\left(A_j^2 + B_j^2\right) \tag{8}$$

and

$$var_i(E[\boldsymbol{y} \mid \boldsymbol{x}]) = 2\sum_{p=1}^{\infty}\left(A_{p\cdot\omega_i}^2 + B_{p\cdot\omega_i}^2\right). \tag{9}$$

where $E(\boldsymbol{y} \mid \boldsymbol{x})$ is the conditional expectation of $\boldsymbol{y}$ when specifying $\boldsymbol{x}$ and var_i as the variance of the ith (the i in ith is the same ordinal number as the i in S_i) input variable x_i ($x_i \in \boldsymbol{x}$) over its entire range of values. A_j and B_j are the common Fourier coefficients of the cosine and the sine series, respectively. The summation in p includes all the harmonics related to the frequency associated with the input variables (Saltelli and Bolado, 1998b).

Each index S_i ranges between 0 and 1 and increases with increasing input variable importance (Cannavó, 2012). FAST is applied in this study to quantitatively analyse the importance of meteorological and water quality factors. In most studies, first-order sensitivity of the parameters has been well used for analysis of non-linear problems.

2.2.7. Construction of the AGA-BPANN-FAST combination proxy model

A simple model is often intuitive and versatile. An optimised single-layer BPANN was established as a proxy model. Further, the FAST method was used to analyse the sensitivity of input variables. The specific steps are as follows:

Step 1: Preliminary data processing
Monthly time-series data (2010–2016) for all variables, i.e. eight meteorological and eleven water quality factors, were acquired from seven sites and examined using

the ADF-test. Some outliers were initially rejected using the t-test method. To unify different data dimensions and improve convergence speed, normalisation is necessary. Max-Min Normalisation was used to linearly transform the raw data:

$$a^* = \frac{a - a_{\min}}{a_{\max} - a_{\min}} \tag{10}$$

where a^* is the normalized input or output data, a is the original data, and $a_{\min}$ and $a_{\max}$ are the minimum and maximum values in the same set of input or output data, respectively.

Normalised historical meteorological and water quality datasets were treated using wavelet transformation to remove noise. The low-frequency component was used for BPANN.

Step 2: AGA-BPANN model building

Three coupled models were established to clarify the intrinsic link between nutrition indicators and meteorological factors. In the first model, ModelChla, which is concerned with how meteorological and other water quality factors influence Chl-a in Hongfeng Lake, all eight meteorological and ten water quality monitoring datasets were adopted as inputs, while the Chl-a dataset was adopted as the output. In the other two models, ModelTP and ModelTN, TP and TN datasets were selected as outputs, respectively, while other variables were assigned as inputs. All models were optimised and the convergence rate of the model was increased using the AGA.

Step 3: Sensitivity analysis based on FAST

A neural network with satisfactory approximation was obtained after Step 2. Sensitivity analysis was applied by using FAST. In order to perform the FAST, the input variable domain has to be set (Cannavó, 2012). The range of all variables was set separately (Table 1). The FAST analysis performs random sampling in the variable domain according to a certain probability density function. A set of input samples is generated for each time, and the output is obtained after modelling. The trained network was run 5000 times and the sensitivity coefficient of each input variable is given by Eqs. (5), (8), (9).

Table 1
The range of all variables after denoising. In order to perform the FAST, the input variable domain has to be set. The FAST analysis performs random sampling in the variable domain according to a certain probability density function. A set of input samples is generated for each time, and the output is obtained after modelling. Running for 5000 times, the sensitivity coefficient of each input variable is given by Eqs. (5), (8), (9).

Variable	Min	Max	Unit
Atmospheric pressure	867.51	882.98	hPa
Atmospheric temperature	−0.77	24.07	C
Humidity	0.72	0.94	[-]
Rainfall	0.00014	0.43	m
Evaporation	0.00057	0.0076	m
Short wave radiation	23.27	82.18	$W \cdot m^{-2}$
Wind speed	1.18	2.87	m/s
Cloud coverage	0.59	1.00	[-]
Transparency	0.81	3.34	m
Water temperature	5.93	27.77	C
pH	7.16	8.93	[-]
COD	1.17	4.56	mg/L
DO	3.35	12.04	mg/L
NH_3-N	0.011	0.71	mg/L
TP	0.016	0.10	mg/L
TN	0.56	2.80	mg/L
Faecal coliform	20	13481	n/L
Fluoride	0.21	0.68	mg/L
Chl-a	0.77	38.91	mg/L

Step 4: Perturbation analysis

With the FAST analysis, some sensitive input variables were identified. Certain perturbations were applied to those sensitive variables and the results were compared with the original data. That is, in each proxy model, the value of an input variable (such as atmospheric temperature) is changed, with this referred to as a perturbation, and the simulated output changes accordingly. The perturbation effect S is defined as:

$$S = \frac{Y^* - Y}{Y} \times 100 \tag{11}$$

where Y^* is the simulated output data and Y is the original output data. The perturbation effect S was applied to analyse the effects of climate change on Chl-a, TP, and TN. A positive S means positive influence while negative S means negative impact.

3. Results and discussion

3.1. Simulation and FAST analysis of water quality

3.1.1. AGA-BPANN model building

The meteorological and water quality data from all sites in each season in the recent 7 years were obtained after denoising. All the datasets are stationary time series. Three interrelated AGA-BPANN models, ModelChla, ModelTP, and ModelTN (with Chl-a, TP, and TN dataset as the output in different models, respectively), were established after repeated training. The results of all three models suggested very good simulations, as shown by the Train R^2, Test R^2, R^2, and MSE (Table 2).

Where R^2 describes how well the model fits all measured values, and R^2 closer to 1 means better fitting effect. Train R^2 describes how well the model fits the measured values used to train and establish the model, and Test R^2 describes how well the model fits the rest of measured values. Train R^2 and Test R^2 values that are close to each other indicate no overfitting. MSE, denoting mean squared error, is a measure of the quality of an estimator, with better results when values are closer to zero. As shown, the simulations for the seven sites and the whole lake area across four seasons were in good agreement with measured data.

Using meteorological and water quality time series that are wide-sense stationary, three AGA-BPANN models can be effectively applied for quantitative assessment of climate change-induced impact on water quality of each site during specific seasons over forthcoming years if water quality conditions remain roughly unchanged. However, these proxy models are based solely on interactions between meteorological and water quality factors. Changes in population, land use, and environmental management, which can strongly affect water quality and global warming, are not considered. When conditions change so that meteorological and water quality time series are not wide-sense stationary any more, new AGA-BPANN proxy models based on new datasets can be needed.

3.1.2. FAST analysis

The FAST analysis (Table 3) shows that in ModelChla, TP has the greatest impact on Chl-a (0.223). The effect of COD, pH, NH_3-N, and TN on Chl-a is also large. In general, the effect of nutrients on Chl-a is very pronounced (0.408), indicating that nutrient inputs have a great impact on algae growth, especially TP. Among physical factors, water temperature has the greatest effect on Chl-a (0.0795).

In ModelTP, TP is significantly affected by Chl-a, water temperature, pH, and TN. Chl-a has the most significant effect on TP (0.529), and TP is also the factor that has the greatest impact on Chl-a. This suggests that phosphorus is closely related to algal growth in

Table 2
Performance of various models. All three models, ModelChla, ModelTP, and ModelTN, are AGA-BPANN proxy models. R^2 and MSE describe how well the model fits all measured values. R^2 closer to 1 and MSE closer to 0 mean better fitting effect. Train R^2 and Test R^2 values that are close to each other indicate no overfitting. As shown, the results of all three models suggested very good simulations.

	Input variables	Output variable	Train R^2	Test R^2	R^2	MSE
ModelChla	All the other variables	Chl-a	0.9962	0.9978	0.9965	9.77e-06
ModelTP	All the other variables	TP	0.9906	0.9941	0.9913	1.28e-06
ModelTN	All the other variables	TN	0.9888	0.9721	0.9810	1.50e-04

phosphorus-restricted waterbodies. The effect of water temperature on TP (0.171) is much more pronounced than other physical factors.

In the case of TN, the input variables pH (0.467), DO (0.271), and NH_3-N (0.122) had significant effects on TN. Since the nitrogen cycle in waterbodies involves multiple valences of nitrogen and the phosphorus valence state is single, TN is controlled more by pH and oxygen content than by other factors.

It is worth noting that the impact of each factor on Chl-a, TP, or TN cannot be illustrated simply by FAST coefficient, albeit the method is effectively applied to quantify and compare effects of various factors on water quality. This is because these factors do not fully reflect the water quality due to the limitations of field monitoring. Some factors affect others that cannot be monitored, which have a direct impact on water quality. Therefore, further analysis and discussion are particularly needed.

Based on the above, as the most important and direct indicators of eutrophication, TP and TN were selected as two factors for perturbation analysis, together with atmospheric temperature as an intuitive measure of climate change. Rainfall was also an important factor affecting lake eutrophication.

3.2. Effects of higher atmospheric temperature on water quality

Extreme weather events include periods of very high temperatures, torrential rains, and droughts. Under the enhanced greenhouse effect, changes can occur in both mean climate parameters and the frequency of extreme meteorological events (Rosenzweig and Solecki, 2014).

Table 3
FAST coefficients of all three models. In general, a larger FAST coefficient means a greater impact on the output. Atmospheric pressure, Atmospheric temperature, Humidity, Rainfall, Evaporation, Short wave radiation, Wind speed, Cloud, Coverage, Transparency, Water temperature are physical factors, while others are chemical or biological factors. TP, Chl-a, and pH have the greatest effect on Chl-a, TP, and TN, respectively. Among physical factors, water temperature always has pronounced effect on water quality.

Input variable	FAST coefficient		
	of ModelChla	of ModelTP	of ModelTN
Atmospheric pressure	1.96e-05	3.42e-04	1.01e-02
Atmospheric temperature	1.10e-02	2.12e-04	3.43e-04
Humidity	7.24e-02	1.69e-04	5.90e-03
Rainfall	2.45e-02	3.35e-05	3.50e-03
Evaporation	2.83e-02	6.62e-05	2.41e-03
Short wave radiation	3.31e-02	1.00e-04	4.10e-03
Wind speed	9.78e-03	3.78e-04	1.79e-04
Cloud coverage	6.71e-04	3.46e-04	1.09e-02
Transparency	1.11e-03	2.34e-02	4.42e-02
Water temperature	**7.95e-02**	**1.71e-01**	2.39e-02
pH	**1.14e-01**	**1.19e-01**	**4.67e-01**
COD	**1.77e-01**	3.95e-03	7.24e-03
DO	7.91e-04	4.74e-04	**2.71e-01**
Ammonia nitrogen	**1.01e-01**	2.64e-02	**1.22e-01**
TP	**2.23e-01**	[-]	7.86e-03
TN	**8.48e-02**	**9.71e-02**	[-]
Fecal coliform	1.94e-03	1.15e-04	5.12e-06
Fluoride	1.98e-02	9.64e-06	3.19e-06
Chl-a	[-]	**5.29e-01**	7.35e-03

Extreme high-temperature events are the short-term manifestations of global warming. The strongest warming (temperature rises about 5 to 7 °C) occurs mainly in the mid-latitudes in boreal summer and autumn (Orlowsky, 2012). This might mean that extreme high-temperature events could strongly affect mid-latitude regions (e.g. China, southern Europe, the United States) in particular seasons, notwithstanding subtle changes in annual average temperature in the short term. Indeed, the frequencies of extreme high-temperature events have increased in most parts of East Asia over the last several decades (Choi et al., 2009). This indicates the possibility of higher temperature events over a short period of time in China, especially in summer and autumn. Effects of higher atmospheric temperature on water quality are worthy of attention.

3.2.1. Impact on algae bloom

In general, the optimal growth temperature for algae is > 15°C and even > 20°C for many species of cyanobacteria. In winter, the temperature is low and any temperature increase greatly improves environmental conditions for algal growth. A 2°C increase in the Guizhou winter average temperature of < 10°C is very beneficial for algal growth (6.00±1.62%). While summer temperatures are high, many algae are already under optimal growth conditions and the continued increase in temperature has less effect on their growth (1.54±0.24%) than in winter (Fig. 3a). Anneville et al. (2015) find that in mesotrophic lakes (Hongfeng Lake is in mesotrophic or eutrophic state), cyanobacteria abundance is strongly influenced by phosphorus concentrations and winter air temperatures; a warm summer does not clearly promote cyanobacteria blooms, whereas a warm autumn does promote cyanobacteria growth in the mesotrophic lakes, and a warm winter is associated with high cyanobacteria abundance. The results in this study could support this view. Therefore, in the context of global warming, the winter bloom deserves more attention.

Analysis of spatial differences in temperature effects on water quality shows that the North Lake area is more frequently affected in summer and autumn than the South Lake area (Fig. 3a). When temperature increased by 2°C in summer and autumn, Chl-a in the North Lake area increased by 2.91±1.28%, compared to 2.09±0.91% in the South Lake area. The North Lake area generally has higher N/P ratios (53.70±8.48) and relatively lower Chl-a content (9.13±3.21) than the South Lake area (N/P 34.70±5.83, Chl-a 11.55±4.30) (Fig. 2c). This suggests that climate change may have a slightly greater impact on more phosphorus-restrictive reservoir regions in summer and autumn.

In winter, the Huayudong site at the junction of the North Lake and South Lake areas was most affected by the temperature rise (increases 7.82% while warming by 2°C, Fig. 3a). The eutrophication conditions in the South and North Lake areas are significantly different and form a large gradient (Fig. 2a, b, c). Water from the South Lake flows to the North Lake via the Huayudong site and material exchanges may occur frequently at that site. In winter, dry season reservoirs receive less exogenous nutrients and their TP load is only 44% of that in the wet season (Wang, 2012). At the same time, endogenous releases are weakened by lower temperatures and inefficient biochemical reactions and the exchange of substances

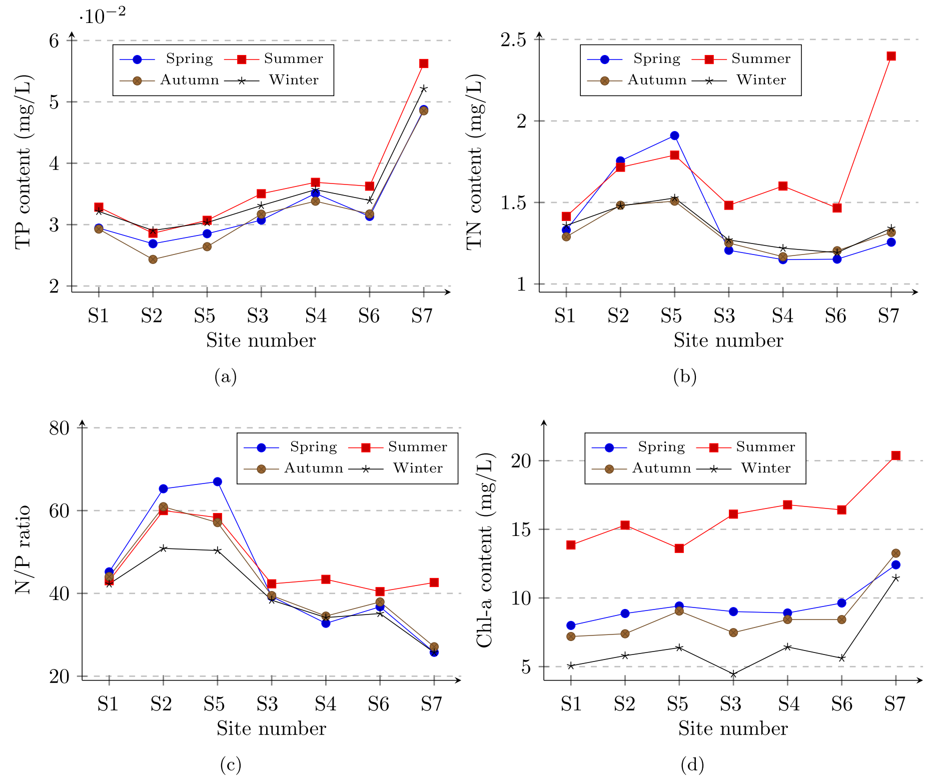

Fig. 2. Nutrients and Chl-a conditions of seven sites in the Hongfeng Lake reservior. S1 - Daba, S2 - Yaodong, S3 - Huayudong, S4 - Houwu, S5 - Pianshanzhai, S6 - Xijiaoshuichang, S7 - Sanchahe. **(a)** Average measured TP content of seven sites for four seasons. **(b)** Average measured TN content of seven sites for four seasons. **(c)** Average measured N/P ratio of seven sites for four seasons. The North Lake area generally has higher N/P ratios (53.70±8.48) than the South Lake area (34.70±5.83). **(d)** Average measured Chl-a content of seven sites for four seasons. The North Lake area generally has lower Chl-a content (9.13±3.21) than the South Lake area (11.55±4.30).

brought by the movement of water in the reservoir area may have a greater impact. More attention should therefore be given to the Huayudong site in “warm winter” years.

Beyond the direct effects on cyanobacterial growth rates, rising temperatures will change many of the physical characteristics of aquatic environments in ways that may be favourable for cyanobacteria (O'Neil et al., 2012). Higher temperatures will decrease surface water viscosity and preferentially promote the sinking of larger, non-motile phytoplankton with weak buoyancy regulation mechanisms (e.g. diatoms) giving cyanobacteria a further advantage in these systems (Wagner and Adrian, 2009; Paerl and Huisman, 2010). Warming of surface waters will increase the frequency, strength, and duration of stratification. This process will generally reduce the availability of nutrients in surface waters favouring cyanobacteria that regulate buoyancy to obtain nutrients from deeper water or that are diazotrophic, therefore have a significant impact on competition within the plankton community in surface waters (Paerl and Huisman, 2008; Paul, 2008; O'Neil et al., 2012). A recent study shows that cyanobacteria dominate phytoplankton assemblages in Hongfeng Lake, especially in the late summer and early autumn (about 97.8%) (Wang et al., 2013). In this study, as temperatures rise by 2°C, Chl-a increases 3.53±1.70% in the whole lake area across the year, and this increase is largely due to the growth of cyanobacterial biomass. It means that cyanobacteria will occupy a larger proportion in Hongfeng Lake than before. The same has been predicted in many studies demonstrating an increase in cyanobacteria blooms with warming (Paerl et al., 2011; Bucak et al., 2017) due to their higher optimum growth temperature (25–35° C) (Robarts and Zohary, 1987).

3.2.2. Impact on eutrophication

Temperature is an important factor affecting chemical reactions and biological effects. Rising temperature can help accelerate various biochemical reactions in stream outlets and water-sediment surfaces, thus increases nutrient inputs to lakes and estuaries by increasing the rate of nutrient release from soils and conversion of nutrients into forms that can be easily used by algae; rising water temperature leads to increased rates of bacterial activity, which deplete oxygen from the water and stimulate release of nutrients already present in the bottom sediments (Jack Brookshire et al., 2015). It means that increasing air temperature tends to accelerate the eutrophication process in water bodies by changing the water temperature (even if the external source of nutrients has become stable) (Xia et al., 2016). Meanwhile, temperature increase is conducive to algal propagation and increased consumption of nutrients. Hence, the warming effect on TP or TN provides a balance between increased algal consumption and accelerated phosphorus or nitrogen cycles.

Higher temperatures promote the endogenous release of phosphorus, which dominates the consumption of algae. The concentration of TP in the surface water of the reservoir thus increases with temperature accordingly (TP increases 0.25±0.18% with warming by 2°C in the whole year). In autumn and winter, TP increases 0.39±0.14% while warming by 2°C, more than in spring and summer (0.11±0.10%, Fig. 3b), likely on account of a destratification event caused by a sudden drop in temperature in autumn. This event took place in a matter of days. Physical and chemical mixing of bottom water with surface water took place. Strong disturbances promoted the release of large amounts of endogenous phosphorus.

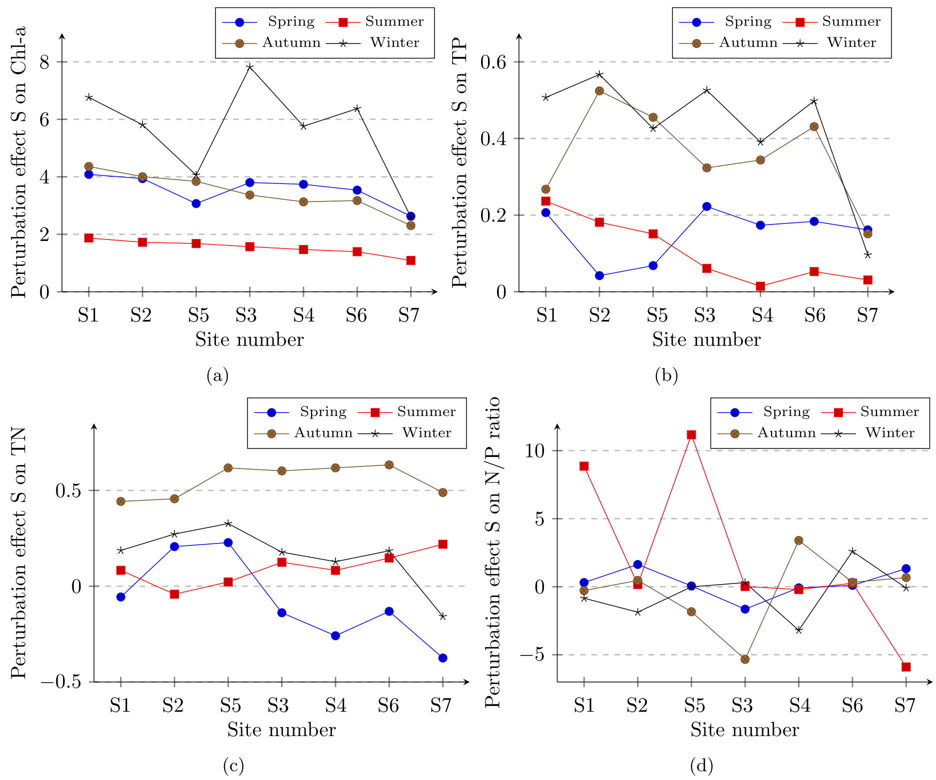

Fig. 3. Perturbation effect S on Chl-a and nutrients while warming by 2°C. S1 - Daba, S2 - Yaodong, S3 - Huayudong, S4 - Houwu, S5 - Pianshanzhai, S6 - Xijiaoshuichang, S7 - Sanchahe. **(a)** Changes on Chl-a content of seven sites for four seasons. While warming by 2°C, Chl-a increases 3.53±1.70% in the whole lake area across the year. **(b)** Changes on TP content of seven sites for four seasons. While warming by 2°C, TP increases 0.25±0.18% in the whole lake area across the year. **(c)** Changes on TN content of seven sites for four seasons. While warming by 2°C, TN increases 0.18±0.27% in the whole lake area across the year. **(d)** Changes on N/P ratio of seven sites for four seasons. While warming by 2°C, N/P ratio increases 6.73±4.74% in the whole lake area in summer.

Phosphorus was carried to surface water and water quality rapidly deteriorated. The increase in average temperature in autumn may accelerate destratification because of higher surface water temperatures. In winter, the water level of Hongfeng Lake drops during the dry season and the concentration of TP in surface water is the highest over the whole year (Fig. 2a). In addition, temperature in winter is low and algae grow less and consume less TP so that TP increases more significantly with temperature in winter (0.49±0.06%). And Sanchahe site is affected most slightly due to the serious degree of eutrophication and the highest algal biomass there (Fig. 2a, a, d).

However, the situation is somewhat different for TN. In autumn, an increase in temperatures may contribute to the increased endogenous release and promote destratification. Algae consume less nutrient than released from the sediments. Therefore, TN increased most (0.55±0.08%) while warming 2°C in autumn (Fig. 3c). However, in other seasons, especially in spring and summer, the increase in temperature may result in a slight decrease (−0.01±0.19%) in TN because higher temperatures are more conducive to the reproduction of algae and the consumption of TN in spring and summer. Higher temperatures will also lead the North Lake area that has higher N/P ratios than the other area to become remarkably restrictive of phosphorus in summer (Fig. 3d, N/P ratio increases 6.73±4.74%). Due to the serious degree of eutrophication at the Sanchahe site (Fig. 2b), the increase in winter temperatures may also cause algal growth and increase TN consumption, and the TN in the Sanchahe site decreased (−0.16%) despite that in other sites increased (0.21±0.07%) in winter (Fig. 3c).

In other words, an increase in temperature will favour endogenous release of phosphorus (0.25±0.18%) more significantly than nitrogen (0.18±0.27%), although this effect is very small without a disturbance (e.g. higher wind speed). Overall, an increase in temperature contributes less to release of endogenous nutrients than expected. This implies that external inputs will be a more important factor in eutrophication over the next few years in the context of global warming. However, it should be noted that although the increase in eutrophication is not remarkable in this study, higher temperatures have pronounced effects on algae growth, and the impact on eutrophication may be underestimated due to more nutrient consumption.

3.3. *Effects of heavy rainfall on water quality*

The 2010–2016 data for meteorological factors represent a stationary time series, indicating that climate change will not have a significant impact on meteorological conditions over the next few years. However, there is no doubt that rainfall events will show greater fluctuations and heavy rains will occur more frequently. Several studies have noted changes in the intensity of short-term rainfall (e.g. sub-daily) related to increasing temperatures (Donat et al., 2016; Luong et al., 2017; Sun et al., 2018). Rainfall dilutes the concentration of nutrients in lakes, while heavy rainfall increases soil erosion and delivery of nutrients, thus leads to increase non-point source pollution.

An increase in storm runoff could cause more non-point source pollution in the context of global warming. Therefore, when rainfall increases, TN loss caused by more water and soil loss increases accordingly (Fig. 4b). TN content in Hongfeng Lake also increases (0.26±0.17% when rainfall increases 50%), particularly in summer

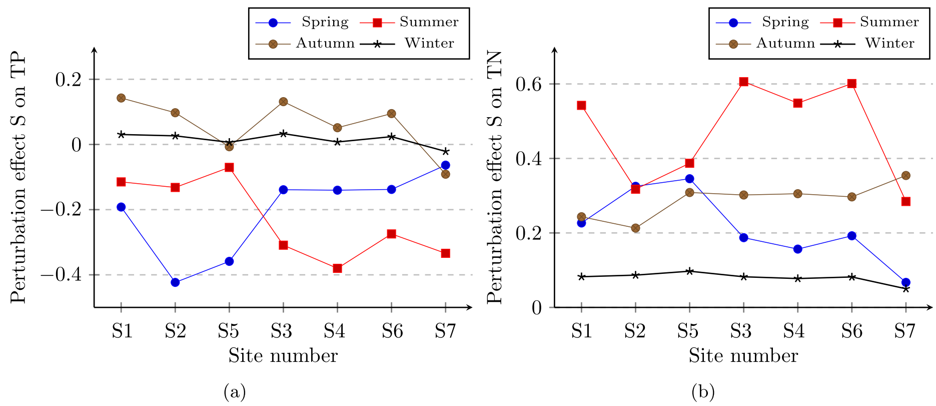

Fig. 4. Perturbation effect on nutrients when rainfall increases by 50%. S1 - Daba, S2 - Yaodong, S3 - Huayudong, S4 - Houwu, S5 - Pianshanzhai, S6 - Xijiaoshuichang, S7 - Sanchahe. **(a)** Changes on TP content of seven sites for four seasons. When rainfall increases by 50%, TP decreases 0.23±0.12% in the whole lake area in spring and summer, and increases slightly (0.04±0.06%) in autumn and winter. **(b)** Changes on TN content of seven sites for four seasons. When rainfall increases by 50%, TN increases 0.26±0.17% in the whole lake area across the year, particularly in summer (0.47±0.14%).

(0.47±0.14%), on account of the greatest summer rainfall intensity in the subtropical monsoon climate zone. In winter, surface runoff intensity is limited owing to the small amount of rainfall; meanwhile industrial wastewater contributes more to TN levels in Hongfeng Lake (Xiao and Liu, 2004) and the effect of agricultural non-point source pollution is relatively low. In recent years, many factories have been shut down in the region and the input of industrial wastewater has decreased. The increase in winter rainfall has the lowest effect on TN (0.08±0.01%). Sinha et al. (2017) show that climate change-induced precipitation changes alone will substantially increase (19±14%) riverine TN loading within the continental United States by the end of the century for the "business-as-usual" scenario. Offsetting this increase would require a 33±24% reduction in nitrogen inputs, representing a massive management challenge. That's not counting likely increases in nitrogen inputs from more intensive agriculture, or from increased human population. And the result in this study is much smaller likely because of different river runoffs and nitrogen fluxes between USA and southwestern China.

Fig. 4a shows that TP is affected by rainfall. The dilution effect of rainfall dominates in spring and summer (−0.23±0.12% when rainfall increases by 50%), the time of peak algal growth. In spring, the TP content in the North Lake area (Daba, Pianshanzhai, and Yaodong sites) was affected by rainfall more significantly (−0.32±0.12%) than that in the South Lake area (−0.11±0.04%). In summer, TP in the South Lake area (Sanchahe, Houwu, and Xijiaohuichang sites) and the Huayudong site were diluted by rainfall more significantly (−0.33±0.05%) than that in the North Lake area (−0.11±0.03%). In autumn and winter, TP increases slightly with the increase in rainfall (0.04±0.06%). The small increase in TP in autumn and winter may be due to the hysteresis effect of TP elution. TP at the Sanchahe site showed a decrease with rainfall over the entire year because TP pollution at this site is most severe (Fig. 2a) and the impact of rainfall on TP is mainly due to dilution.

In most catchment areas in Denmark, climate change impacts on the TP losses similarly showed pronounced seasonality, and the modeled changes in TP losses are expected to be the highest in late winter (February and March) and early summer (May and June), whereas the TP losses decrease in autumn (September and October) (Jeppesen et al., 2009). It is somewhat different from the results in this study. In summer, TP in the whole lake area is mainly diluted by changing rainfall and TP losses decrease across the entire reservoir area. Lakes in southwestern China will be more greatly affected by dilution than in Denmark likely due to different climate conditions. Jennings et al. (2009) found that in Ireland, the changes include large increases in TP loading in the winter and early spring followed by reductions during the summer months in the absence of any land use or population change. A great similarity exists in the result and this study. Simulations using the SWAT model in another UK catchment reported similar increases in winter and decreases in summer TP loading in the global warming context (Bouraoui et al., 2002). It should be noted that, all of these results and the current study, however, were based solely on changes in rainfall and temperature. The potential exacerbation and mitigation of climate change impacts by concurrent change in population, land use, and land management were not taken into account. But Jennings et al. (2009) also pointed out that the increase in annual TP loads which is attributable to climate change is greater than that arising from population increase or potential land use changes. That means, although the simulation results show that the positive effects of increasing temperature and rainfall on nutrients are not pronounced, the impact of global warming on lake eutrophication remains crucial.

The hysteresis effect on nutrients is proved by calculating and plotting the cross-correlation function between rainfall and TP time series at each site. Fig. 5 shows the results for all sites. When the *lag* (τ) is 0, the cross-correlation coefficients of all sites are within two standard deviations or not maximum (Fig. 5). When the *lag* is not zero, there is always a certain τ for all sites so that coefficients are maximum (max cross-correlation coefficients 0.25±0.07). This indicates that the response of TP to rainfall has an evident lag. Fig. 6 shows that the hysteresis effect on TN is more pronounced, with larger coefficients (0.40±0.07), indicating common effects of time delay on non-point source pollution. Meanwhile, this hysteresis effect has both positive and negative effects on TN and also shows that the relationship between rainfall and TN is complex.

In conclusion, since Hongfeng Lake is a phosphorus-limited lake, phosphorus source pollution caused by precipitation is easily consumed by algal growth in the season when conditions are appropriate. However, that also means that excess TN may be more difficult to reduce by algal consumption. A more random heavy precipitation event will therefore have a greater impact on nitrogen source pollution in the climate change context. In other words, non-point source pollution brought by rainstorms will lead to increase in TN and the lake may become more restrictive of phosphorus. The results above reveal that higher temperatures will lead the North Lake area to be more phosphorus-restrictive than before in summer and also have a slightly greater impact on algae growth in more phosphorus-restrictive reservoir areas in summer and autumn. This means that

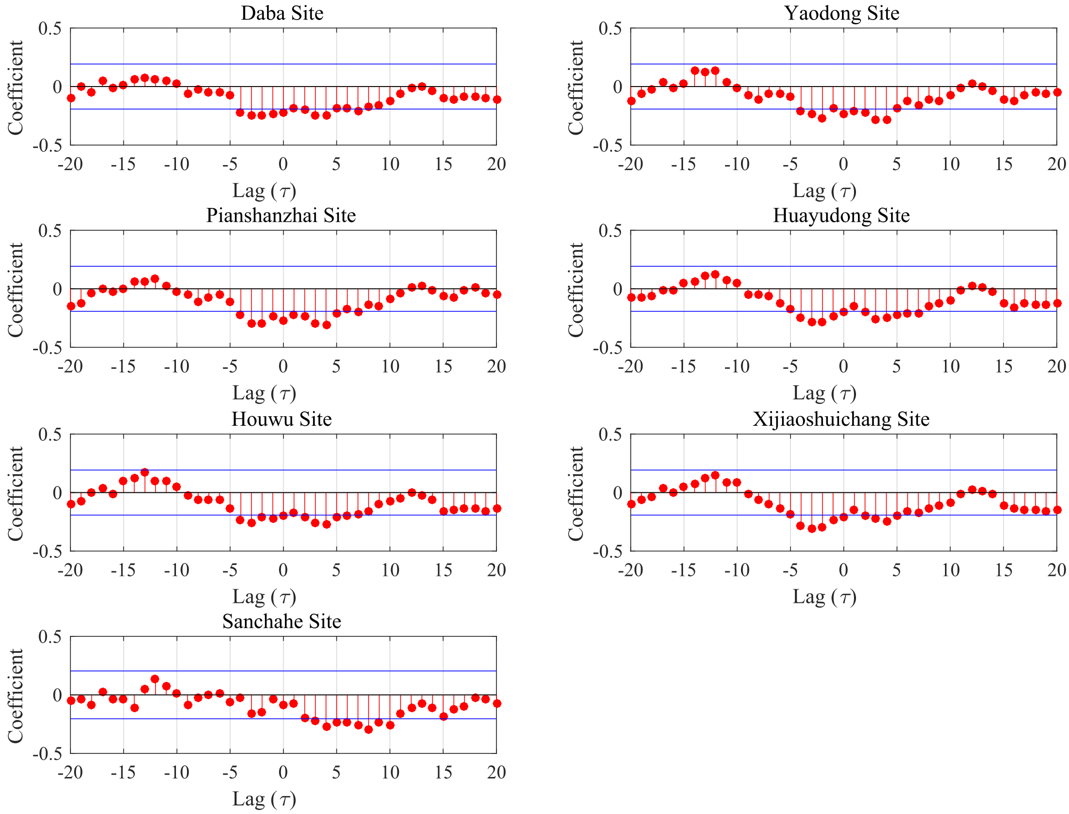

Fig. 5. Results of cross-correlation test (TP and rainfall). When the *lag* is not zero, there is always a certain τ for all sites so that coefficients are maximum (0.25±0.07). It indicates that the response of TP to rainfall has an evident lag.

climate change may be beneficial for the occurrence of toxic, non-diazotrophic cyanobacteria blooms in the North Lake area, such as *Microcystis* (O'Neil et al., 2012).

3.4. Effects of human activity on water quality

TP concentrations in sediments ranged from 973.36 to 2334.18 mg/kg, with a mean concentration of 1635.87 mg/kg (dry weight), and it was evident that the phosphorus level in sediments was high compared with results from other eutrophic lakes such as Chaohu and Xihu Lakes (Jiang et al., 2011). When external environmental factors change, agitation of sediments causes phosphorus to be released in large quantities, with this being the main cause of large-scale algal blooms. In addition, TP can increase because of cultivation, fertilisation, and sudden phosphorus leakage incidents from risky enterprises. However, the perturbation analysis results above show that the increase in endogenous releases caused by higher atmospheric temperatures only leads to very slight increases in both TP and TN. External inputs, which are closely related to human activities, therefore contribute more to the increase in nutrients than endogenous release. Increased nutrient content is conducive to algal growth and Chl-a increases.

When TP discharged into the reservoir increases, all seven sites are significantly affected across the entire year (3.20±1.60% when TP increases by 5%, Fig. 7a). Throughout the year, the South Lake area is more greatly affected by TP (3.21±1.47%) than the North Lake (3.01±1.41%) because the former is relatively rich in N and the N/P ratio is higher, while the latter is relatively rich in P and the N/P ratio is lower, external P inputs can make the N/P ratio of the South Lake be closer to 7.2:1, which is favorable to growth of blue-green algae (Smith, 1983); thus, TP can affect the South Lake area more significantly. An increase in TN will also lead to an overall increase of Chl-a in the reservoir area across the entire year (2.38±1.51%, Fig. 7b), but the effect is smaller than it is for TP. Throughout the year, the North Lake area is more strongly influenced by TN (2.86±1.63%) than the South Lake (1.84±1.01%).

In winter, the entire reservoir area is strongly affected by external nutrient loading (5.38±1.36% when TP increases 5%, 4.27±1.49% when TN increases 5%), with the largest increase in Chl-a in Huayudong as TP increases (7.42%, Fig. 7a). As is mentioned above, the Huayudong site was also most affected by the temperature rise. This implies that the Huayudong site, which has a higher TP than the North Lake area and a higher TN than the South Lake area, may be the most significant potential breeding ground for algal blooms during warmer winters.

Paerl et al. (2001) pointed out that dual N and P input reductions are usually required for effective long-term control and management of harmful blooms. From well-established, but nonlinear, positive relationships among nitrogen and phosphorus flux, and phytoplankton primary production (Rabalais, 2002), people knew that the important measures of controlling had two methods: (a) reducing the inputs of N and P; (b) reducing the input of P so that the ratio of N to P diverged greatly from the equilibrium ratio (Smith, 1985, 1990). Controlling the concentrations of P and N in lake water, especially the concentration of P, is the main method to control the growth of blue-green algae. The severe deficiency of P leads to decrease of population of blue-green algae, even extinction. But when the decrease the input of P is within the limits of tolerance of the creature, algae can persist weakly (Smith, 1983). In that case algae still bring about the pollution of water quality. Blue-green algae needs a high N concentration reaching to 5 mg/L of N (TN in the whole lake area is 1.44±0.27 mg/L), and this concentration cannot be

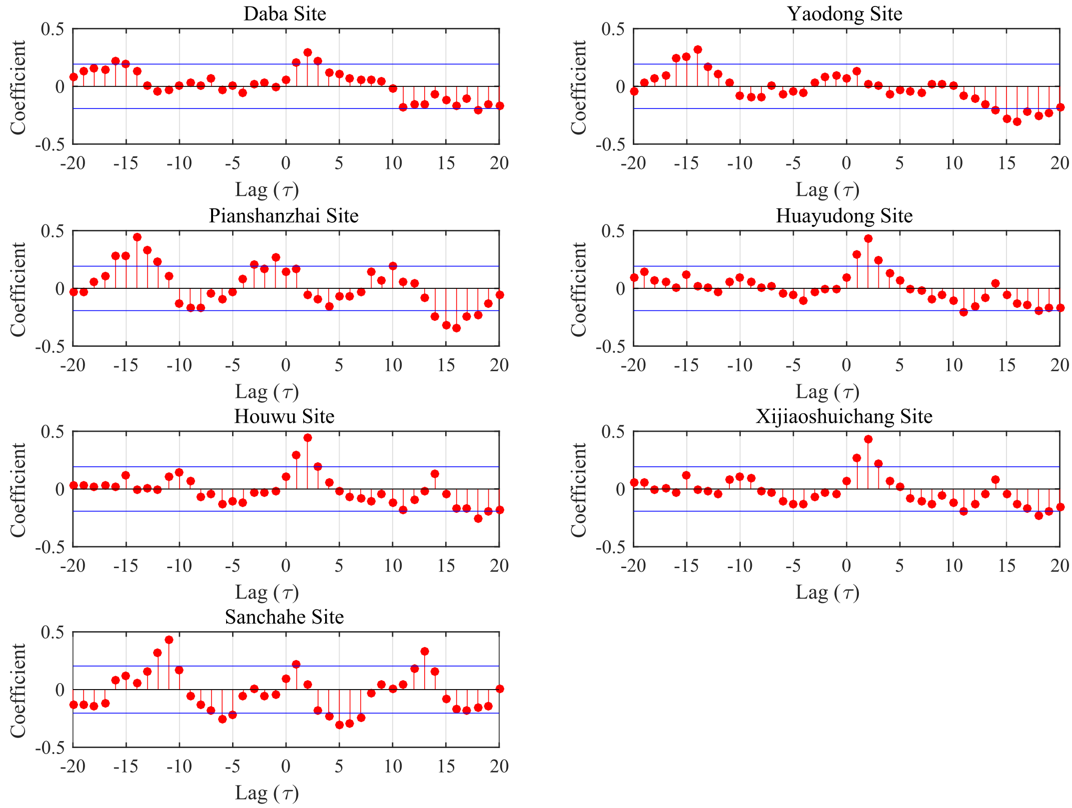

Fig. 6. Results of cross-correlation test (TN and rainfall). When the *lag* is not zero, there is always a certain τ for all sites so that coefficients are maximum (0.40±0.07). It indicates that the response of TN to rainfall has an evident lag. Positive and negative coefficients may imply that hysteresis effect of elution and dilution exists, respectively. The relationship between rainfall and TN is complex.

obtained only depending on the nitrogen fixation of algae, therefore the restriction on importing N still has a definite meaning (Chen et al., 2009). The results based on coupled models highlight that in the Mediterranean basin, reduced nutrient loading in a warming world may play a crucial role in offsetting the effects of temperature on phytoplankton growth (Bucak et al., 2017). In this study, a similar trend emerged in the analysis conducted using a proxy model (ModelChla) also. When the temperature rises by 2 °C, the positive effects of temperature in Hongfeng Lake area can be completely offset if 7.5% TP or 22.16% TN is reduced individually, or 3.5% TP and 10.5% TN are reduced simultaneously. This also implies that the synergy of TP and TN is critical to algae growth.

Controlling the pollution sources from the bottom soil, ship, and cultivation in the lake can effectively decrease the endogenous loads. Regular excavation of the surface layer of bottom soil can reduce considerably the input of P, and the phosphorous sedimentary substances are not easy to release P after excavating (Chen et al., 2009). Reducing domestic wastewater and industrial sewage discharge,

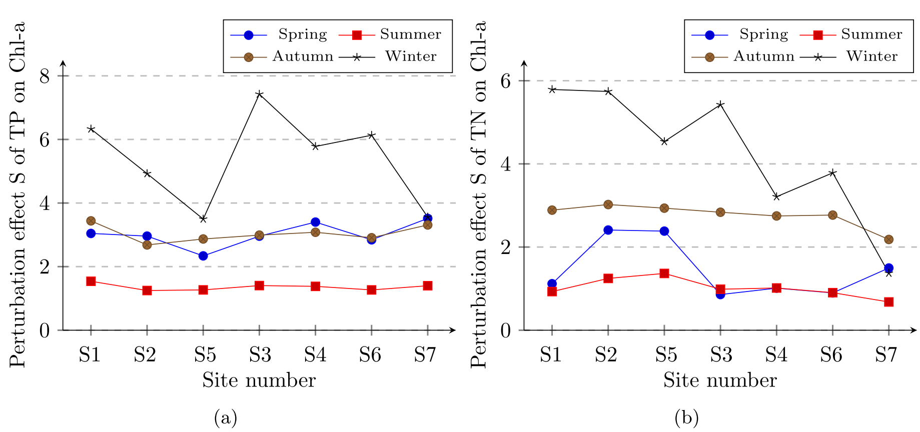

Fig. 7. Perturbation effect on Chl-a when nutrients increase by 5%. S1 - Daba, S2 - Yaodong, S3 - Huayudong, S4 - Houwu, S5 - Pianshanzhai, S6 - Xijiaoshuichang, S7 - Sanchahe. **(a)** Changes on Chl-a content due to TP increase of seven sites for four seasons. When TP content increase by 5%, Chl-a increases 3.20±1.60% in the whole lake area across the year. The South Lake area is more greatly affected by TP (3.21±1.47%) than the North Lake (3.01±1.41%). **(b)** Changes on Chl-a content due to TN increase of seven sites for four seasons. When TP content increase by 5%, Chl-a increases 2.38±1.51% in the whole lake area across the year. The North Lake area is more strongly influenced by TN (2.86±1.63%) than the South Lake (1.84±1.01%).

increasing the nutrient-use efficiency in agriculture, and promoting application of sewage treatment are effective measures to control exogenous nutrient inputs.

In summary, external nutrient inputs contribute more to eutrophication than endogenous release in the context of global warming. TN will have a greater influence on more phosphorous-restricted reservoir regions, while TP will have a greater impact on reservoir regions where phosphorous-restriction is relatively weaker. Reducing external inputs and controlling endogenous releases will help alleviate eutrophication.

4. Conclusion

1. A proxy model reflecting seasonal variations and spatial heterogeneity was established based on AGA-BPANN-FAST. A new method FAST was well used to understand the importance of various inputs on output in a black box model. Using meteorological and water quality time series that are wide-sense stationary, the model can be effectively applied for quantitative assessment of climate change-induced impact on water quality of each site during specific seasons over the forthcoming years if water quality conditions remain roughly unchanged. Machine learning method is proved to be effective and promising in lake ecology.
2. Plateau deep-water lake, with a long retention, weak ability to purify pollutants entering the lake, and strong seasonal stratification, is vulnerable to climate change. Overall, climate change is expected to cause algal blooms and nutrient enrichment, notwithstanding weak effects on TP and TN, and may lead the North Lake area to be more phosphorus-restrictive than before. Non-point source pollution has a lag that may have unintended consequences.
3. External nutrient inputs (e.g. endogenous release, sudden phosphorus leakage, or factory discharges) will significantly promote algal growth in Hongfeng Lake. Reducing nutrient loading will effectually offset the impact of temperature on algae growth. Positive effects of 2 °C increase in temperature can be completely offset if 7.5% TP or 22.16% TN is reduced. Limiting exogenous inputs of nutrients and controlling their endogenous release are key to alleviating lake eutrophication.

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